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aHD205 .L44 1992



## Assessing Risks to Resident Salmonid Populations from Land-use Activities

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APR 06 2000

Cataloging Prep

A paper presented at the 1992 SAF National Convention in Richmond, Virginia

### **ABSTRACT**

Many salmonid populations of the intermountain region of North America are threatened by habitat degradation resulting from changing landuse practices. Public lands managed by the USDA Forest Service and Bureau of Land Management comprise a significant portion of the remaining suitable habitat. Land-use decisions within the public lands must consider the potential effects on sensitive species. A computeraided decision-support system is under development that will help managers anticipate impacts of management decisions on resident trout populations. Central to this system is a Bayesian belief network that links watershed models with population viability models. Recognizing that such linkages are imprecise, this system provides probabilistic risk assessments of land-use impacts given uncertain knowledge.

### 1.0 Introduction

Many of the native trout and salmon species in the intermountain region are in jeopardy. Recently, both species of salmon native to Idaho were added to the Federal threatened and endangered species list. Less visible, but no less threatened or important are the resident trouts. The American Fisheries Society list of endangered, threatened or fishes of special concern includes 9 species or subspecies of resident trout from the intermountain states (MT, ID, NV, WY, UT). These include six subspecies of cutthroat trout (*Oncorhynchus clarki spp.*), redband trout



(O. mykiss gibbsi), bull trout (Salvelinus confluentus), and Montana grayling (Thymallus articus montanus).

The principal threat to these populations is loss of habitat resulting from a combination of changing land-use patterns and instream alterations over the last 150 years. Logging, mining, agriculture (including livestock grazing), and urbanization have degraded watersheds, while irrigation and hydroelectric dams or diversions have reduced the quantity and quality of available habitat. In addition, overharvest, stocking of exotic species, six years of drought, and widespread fires have compounded the problem.

The resulting decline in suitable habitat has fragmented and isolated native trout populations. Many of our strongest populations remain in wilderness areas that retain pristine habitat.

Outside of wilderness, much of the best remaining trout habitat lies within public lands administered by the USDA Forest Service or the USDI Bureau of Land Management. An easy solution to habitat preservation is to exclude these lands from detrimental activities, but such proposals likely are unacceptable. Federal law requires that public lands be managed for multiple purposes. Thus, fish and wildlife needs are balanced against commodity interests.

The Forest Service has developed specific procedures for dealing with threatened, endangered, and sensitive species--the so called TES species. Forest Service regulations require that a Biological Evaluation or Assessment be prepared for each activity within the Forests that might affect a TES species. For trout populations, such activities include timber sales, road construction, mining leases, and grazing allotments. It is the responsibility of the forest supervisor and his staff to assess the threat posed by the activity; each assessment produces a "determination of effect."

Given the large number of assessments required of each forest and the broad range of situations to consider, a methodology is needed that is

- rapid--can be completed expeditiously,
- general--does not require extensive site-specific data, and
- defensible--biologically sound, rigorous and logically consistent.

In the remainder of this paper, I describe an assessment tool designed to meets these needs.



### 2.0 Overview of Decision-Support System

We are developing a suite of models and data bases that comprise a decision-support system. It has three major components: a watershed model, a population viability model, and a Bayesian belief network.

### 2.1 Watershed Model

Model is a misnomer here as this part of the effort is much broader. We anticipate compiling a collection of GIS data bases and models that will allow us to project management activities onto the landscape and quantitatively estimate changes in riparian and instream conditions. I won't discuss this model other than to say that its development is an interdisciplinary effort involving hydrologists, geomorphologists, and fish habitat specialists.

### 2.2 Population Viability Model.

This model might take a variety of forms that allow us to evaluate the probability of persistence and other statistics of interest. The simplest case would be based on a population projection matrix with stochastic rates of the form,

$$N(t) = M \times N(t-1)$$

where

$$N(t) = \begin{bmatrix} juveniles \\ adults \end{bmatrix} \qquad M = \begin{bmatrix} 0 & \alpha \\ \beta & \gamma \end{bmatrix}$$

 $\alpha$  = reproductive rate

 $\beta$  = juvenile survival rate

 $\gamma$  = adult survival rate

The parameters,  $\alpha$ ,  $\beta$ , and  $\gamma$  are correlated random variables which each follow a Johnson's  $S_b$  distribution (Johnson and Kotz 1970). By knowing N(t) and examining M, we can make probabilistic predictions about the size of the population in the future.

Let me emphasize that the watershed model and the population viability models are very different entities. The watershed model is empirically based, large, and data-intensive; understanding requires hours of effort. In contrast, the population model is more mathematically elegant and



parsimonious. A competent biometrician could grasp the basic concepts of the model in a manner of minutes; to understand its behavior would take mere hours. Our challenge is to link these two entities in a logical and rigorous manner.

### 2.3 Bayesian Belief Network.

There are two key aspects to linking land-use changes to fish. First, the relationship between watershed characteristics and fish population dynamics is very complex. Second, where relationships exist, they are very imprecise. We have decided that the best way to systematically mimic this linkage in a decision-support system is through the use of a Bayesian Belief Network (BBN). The network is the primary vehicle for drawing inferences about landscape impacts on fish, and it provides the linkage between the watershed model and the population viability model.

### 3.0 Background on Bayesian Belief Networks

BBN's are a relatively new development in the field of artificial intelligence; examples of their use in natural resource management are almost nonexistent (Haas 1991 is a notable exception). Therefore, a brief explanation is warranted.

Pearl (1988) formally defines a BBN as,

"A directed acyclic graph in which each node represents a random variable that can take on two or more possible values, and the arcs signify the existence of direct influences between linked variables. The strength of these influences are quantified by forward conditional probabilities."

This sounds more complicated than it is, as a simple example will illustrate. Figure 1 shows a directed acyclic graph containing four nodes. The nodes represent riparian vegetation, woody debris, pool complexity, and juvenile rearing conditions. The directed arcs signify that the character and abundance of riparian vegetation and woody debris contributes to stream complexity, which in turn influences juvenile rearing conditions.

The nodes represent system properties that can be characterized using discrete random variables. Each random variable, or node, can take on a range of values. To simplify matters, I have divided each variable into three or four discrete ranges. At any given point in time, the state of the



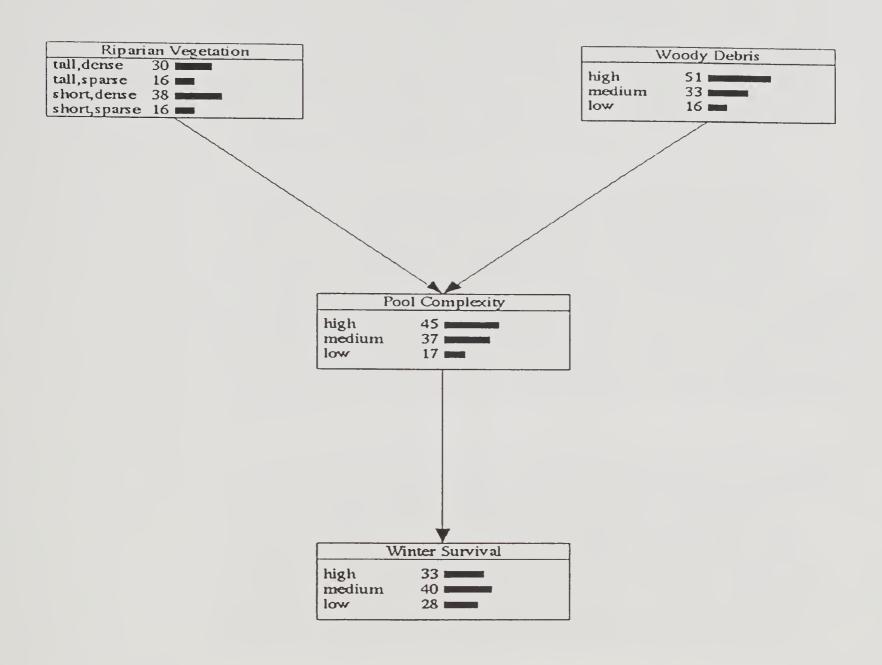


FIGURE 1. Graph of a simple, four-node Bayesian Belief Network

system is reflected by the set of random variables,  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_4$ , which is a subset of all possible combinations of  $X_1$ - $X_4$ . Although the system can be in only one state at a given time, we may be uncertain of its nature. Thus, we express our uncertainty as a belief vector, represented here by the histogram at each node. The value attached to each level within each node represents the degree to which we believe each level is the true system state.



In a nutshell, the purpose of a BBN is to rigorously track these belief vectors and systematically update them as information is added to the system. It does this using the calculus of conditional probability first articulated by Bayes (1763), and adapted to this purpose by Andersen et al. (1987) and others. Constraints on space prohibit me from covering the details of calculating and updating BBN's. Readers are referred to Olson et al. (1990) and Haas (1991) for an introduction to BBN's; Pearl (1988) provides more comprehensive coverage.

One feature of a BBN is that information is passed along two separate pathways. Thus, our belief about a certain node can originate from a parent node (causal evidence) or a child node (diagnostic evidence). Furthermore, the network recognizes where information enters the system and updates all other nodes according to the information received, but blocks the updates from changing the belief vector of the originating node. In this manner it prevents circular reasoning (e.g., evidence for smoke leads to increased belief in the presence of fire, which leads to increased belief in the presence of smoke, which leads to increased belief in fire, etc.).

At the heart of the BBN are conditional probability matrices that define the relationships between nodes. Table 1 provides an example from our four-node network. The values within the matrix can come from empirical evidence, or if that is lacking, from expert opinion. (The numbers in Table 1 came from neither source; I made them up for this illustration.) These link matrices are rich in information. Once the structure of a causal network has been defined, the bulk of the effort is dedicated to developing reasonable estimates for the link matrices.

### 4.0 Overview of BBN for Risk Assessment

If a BBN is to be useful in assessing risks to trout, it must be comprehensive--which implies considerable complexity. Figure 2 depicts a proposed framework for a BBN that could be used to link management activities to the viability of resident trout populations. Land-use activities reside at the root level (i.e., no parent nodes) along with general watershed features. These nodes impact instream habitat characteristics and riparian vegetation, which impacts various stages of the trout life cycle. Life cycle impacts in turn affect the parameters of the viability model.



Table 1. Conditional Probabilities Linking Woody debris and Riparian Vegetation to Pool Complexity

Low	0.09 0.44 0.47	0.07 0.31 0.62	0.06 0.36 0.58	0.02 0.17 0.81	high medium low	
Woody Debris Medium	0.57 0.40 0.03	0.29 0.62 0.09	0.33 0.57 0.10	0.15 0.50 0.35	high medium low	Pool Complexity
High	tall, dense 0.86 0.12 0.02	tall, sparse 0.71 0.25 0.04	short, dense 0.57 0.37 0.06	short, sparse 0.23 0.47 0.30	high medium low	

Riparian Vegetation



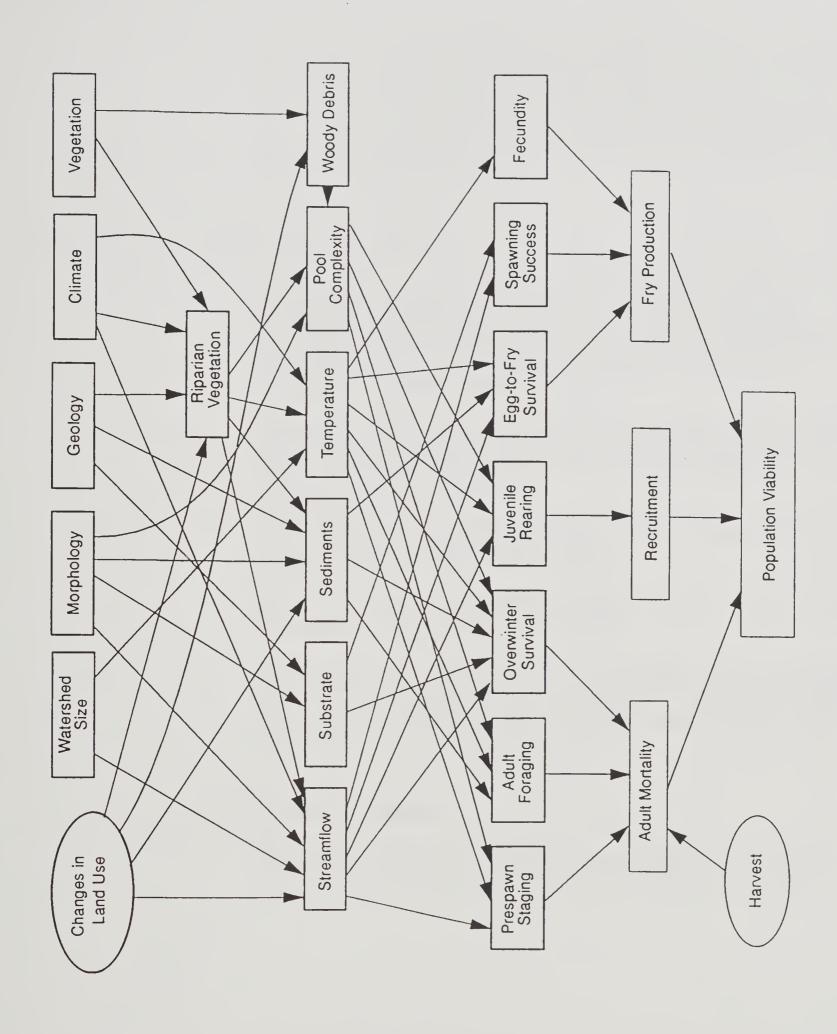


FIGURE 2.

Graph of BBN Linking Land-use Changes to Trout Viability



In coming months, Forest Service researchers and others will be trying to formalize the components and linkages within this BBN and develop estimates of the conditional probabilities needed to define the link matrices. This exercise will not only produce a useful assessment tool, it will also be very useful in identifying significant information gaps that should be targeted by research.

### 5.0 Literature Cited

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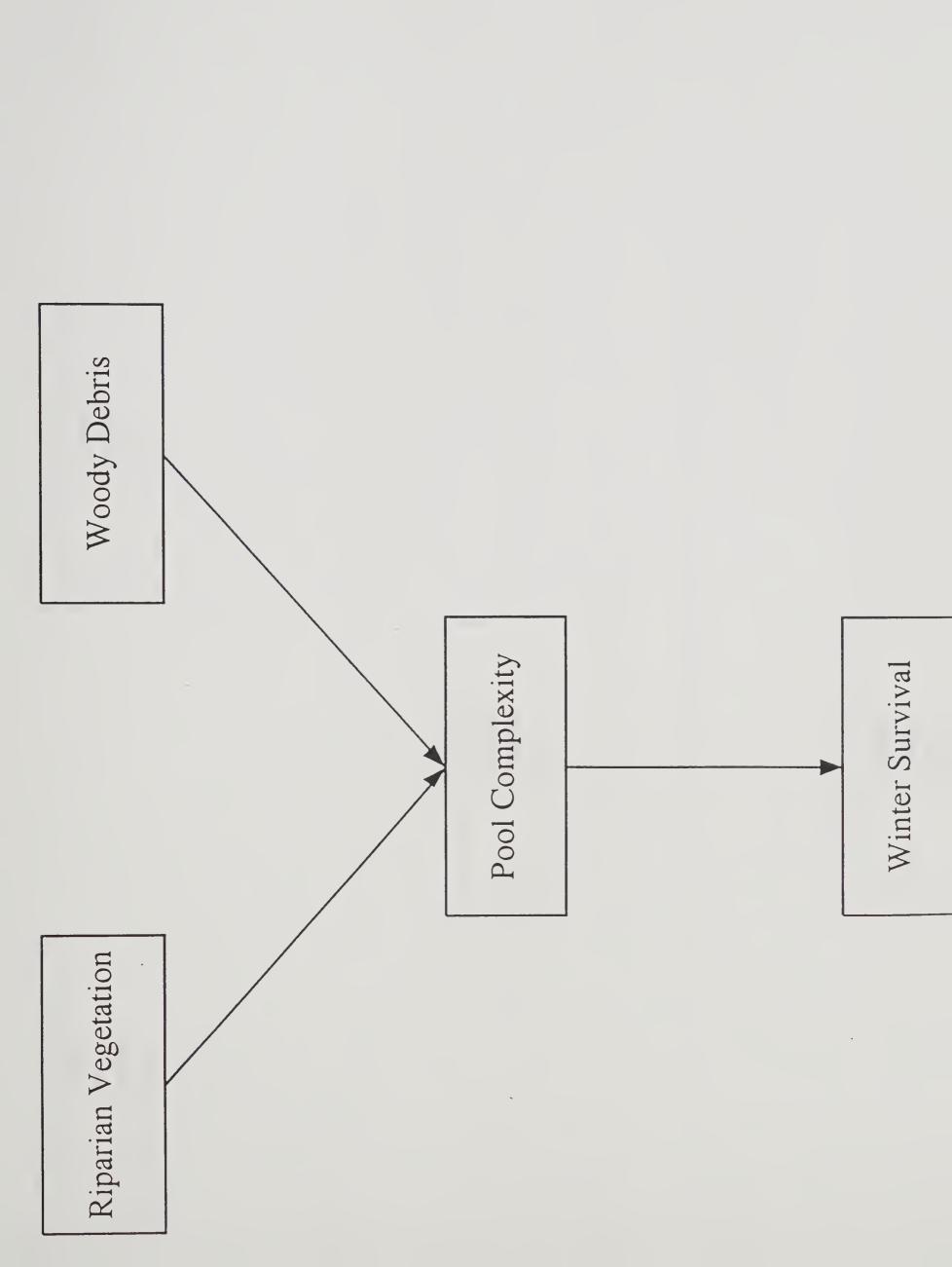
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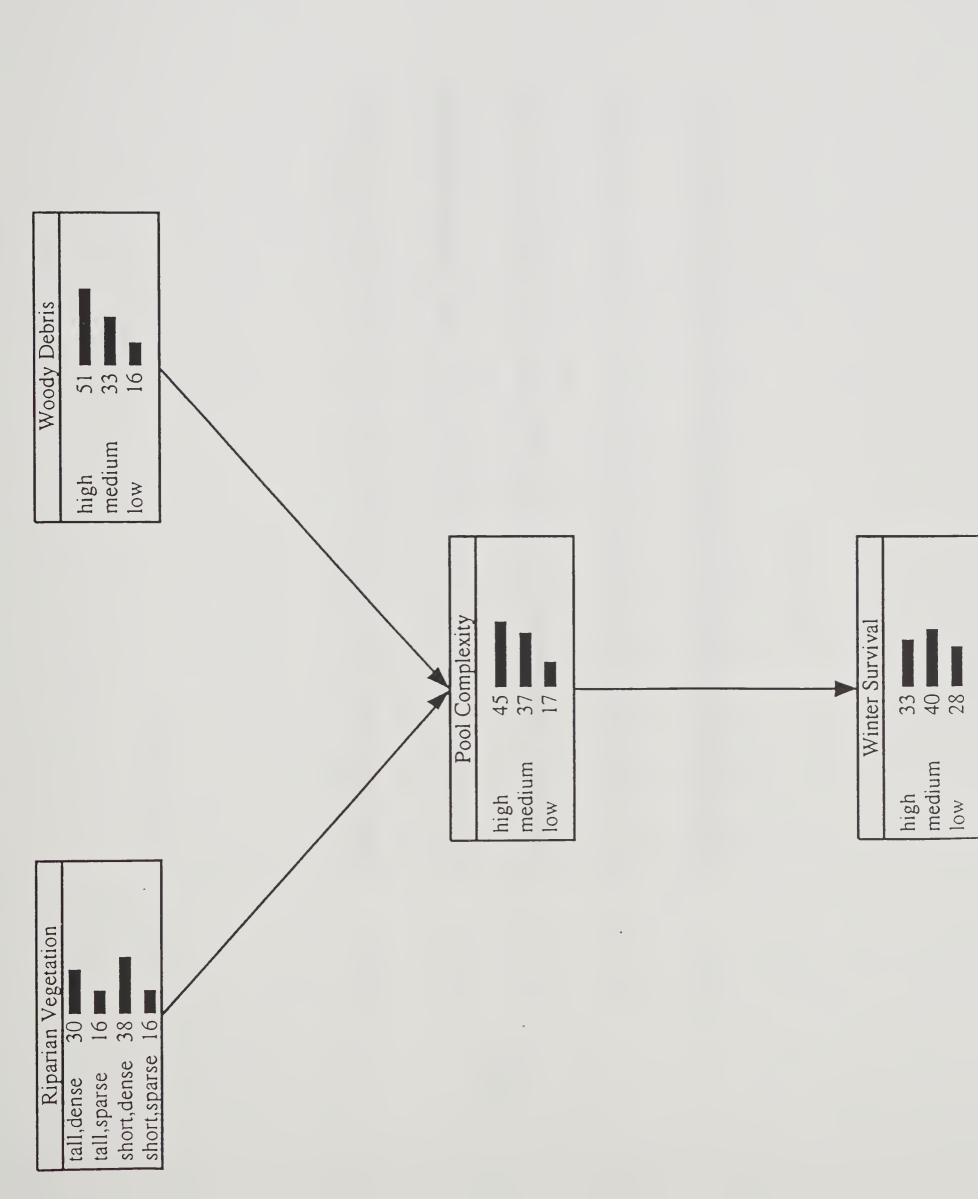
### 6.0 Additional Figures

The attached figures and tables without explanation are provided as copies of the overheads used in the oral presentation of this paper.











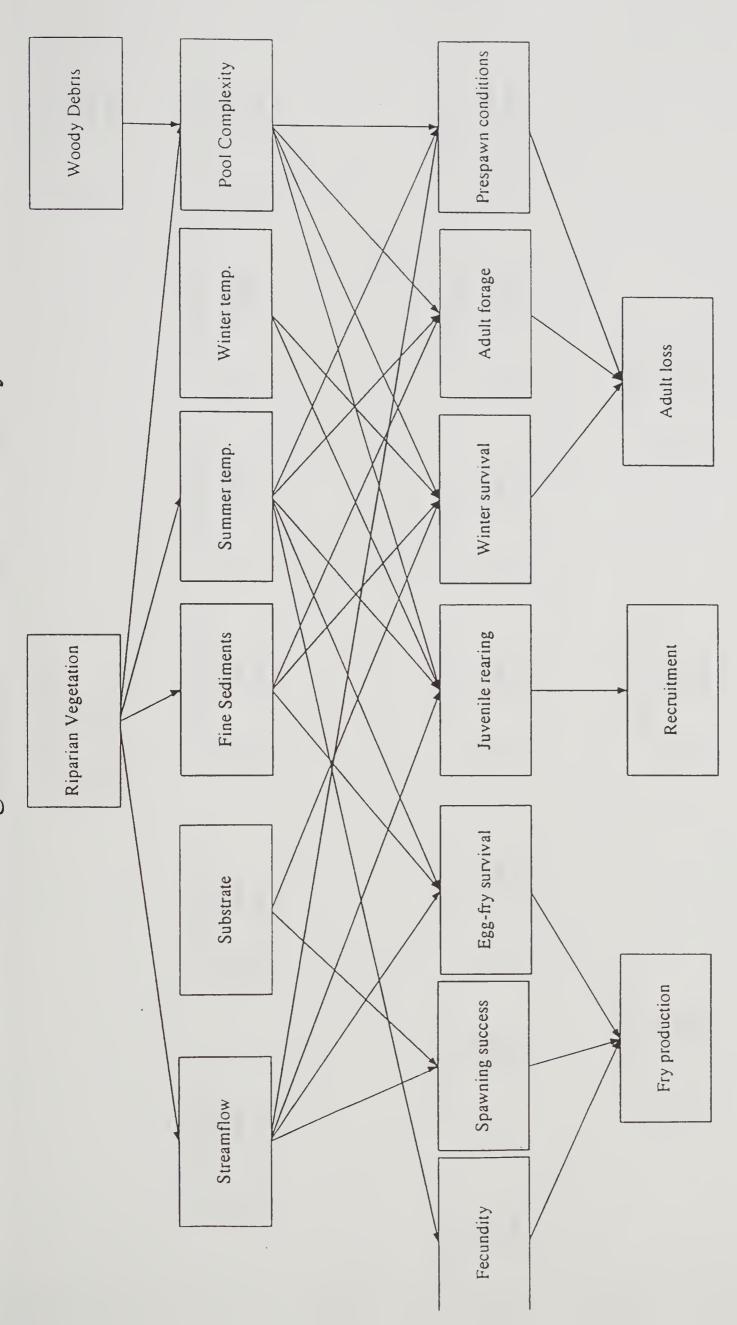
Example 1. 4 x 3 x 3 matrix

		2	<b>25</b>	K	3	06 W
	marginal	0.57         0.40         0.03         0.44         0.47         0.51         0.32         0.17           0.47         0.46         0.07         0.13         0.43         0.45         0.45         0.45	0.29         0.09         0.07         0.31         0.62         0.35         0.39         0.25           0.33         0.57         0.10         0.07         0.42         0.51	0.57         0.37         0.06         0.33         0.57         0.10         0.06         0.36         0.58         0.32         0.43         0.25           0.56         0.33         0.11         0.29         0.61         0.10         0.06         0.45         0.49	0.15         0.50         0.35         0.02         0.17         0.81         0.13         0.54           0.15         0.27         0.02         0.23         0.75	0.34 (2.0.52)         0.14         0.06 (2.0.32)         0.62         0.33         0.37 (2.30)           high medium low         high medium low         high medium low         high medium low         high medium low
		); (0	980	0.32	0.13	©.33 high
Woody Debris		0.47	0.62	0.58	0.81	<b>D.62</b>
	No	0.43	0.31	0.36	0.47	0.06 (0.32 0.62 high medium low
		0.09	70.0	0.06	0.02	<b>0.06</b> high
		6.03 0.07	0.00	0.10	0.35	<b>D.14</b>
	medium	0.46	0.62	0.57	0.50	0.34 2.0.52 2.14 high medium low
		0.57	<b>0</b> .29 (	<b>0.33</b>	0.15	<b>6.34</b> high
	high	1100000	0.04	0.06		0 (5)
		<b>0.12</b> 0.20	<b>0.25</b>	0.33	0.35	#0.26 0.15 medium low
		0.86 0.12 0.02 0.73 0.20 0.06	<b>0.71 0.25 0.04</b> 0.60 0.29 0.11	0.57	<b>0.23 0.30 0.47</b> 0.32 0.35 0.33	0.59 0.26 0.15 high medium low
		tall, dense	tall, sparse	short, dense	short, sparse	marginal
Riparian Vegetation						

Pool complexity

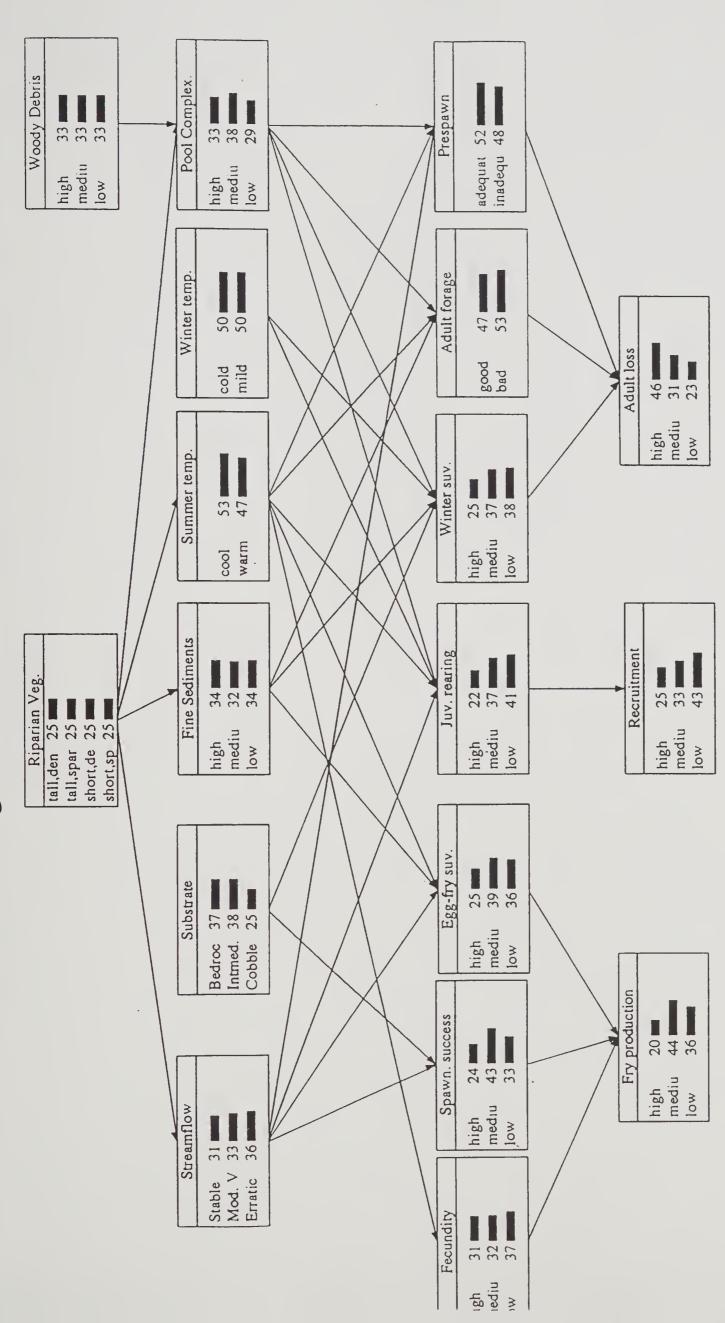


# BBN Linking Habitat to Fish Life History

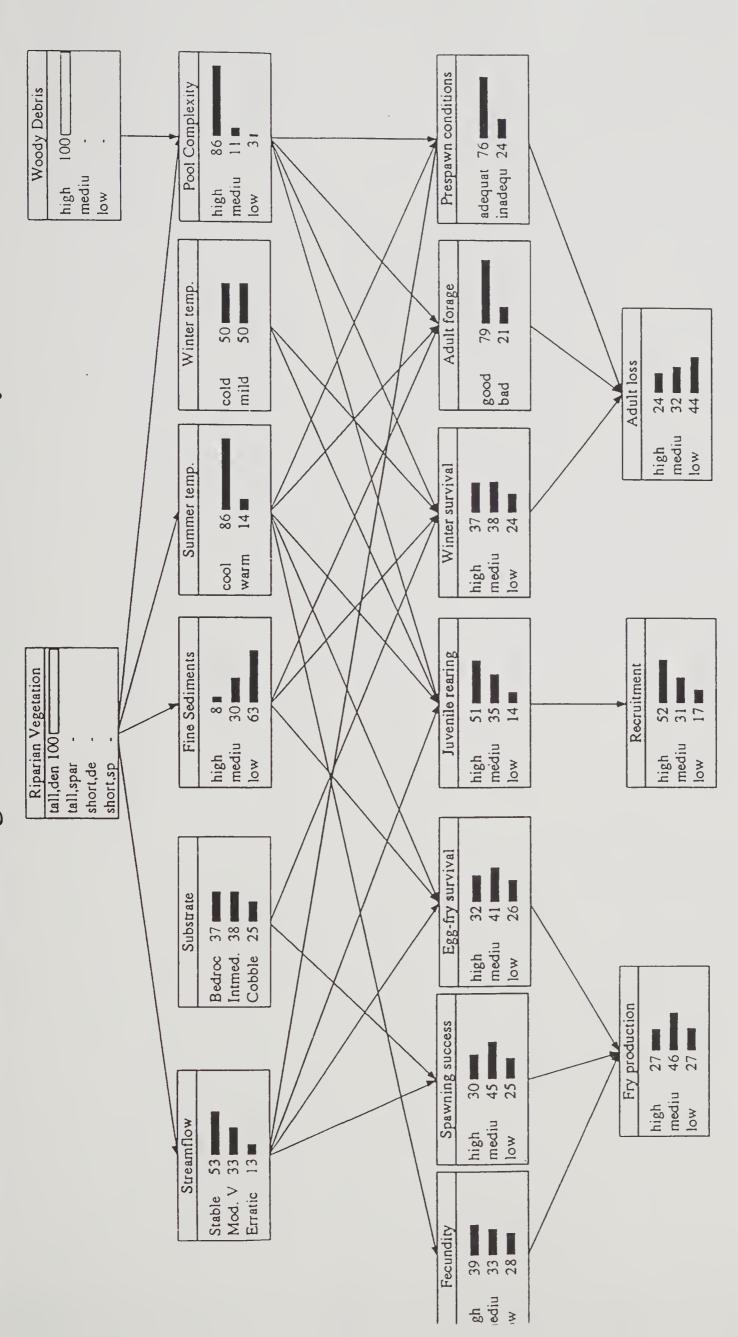




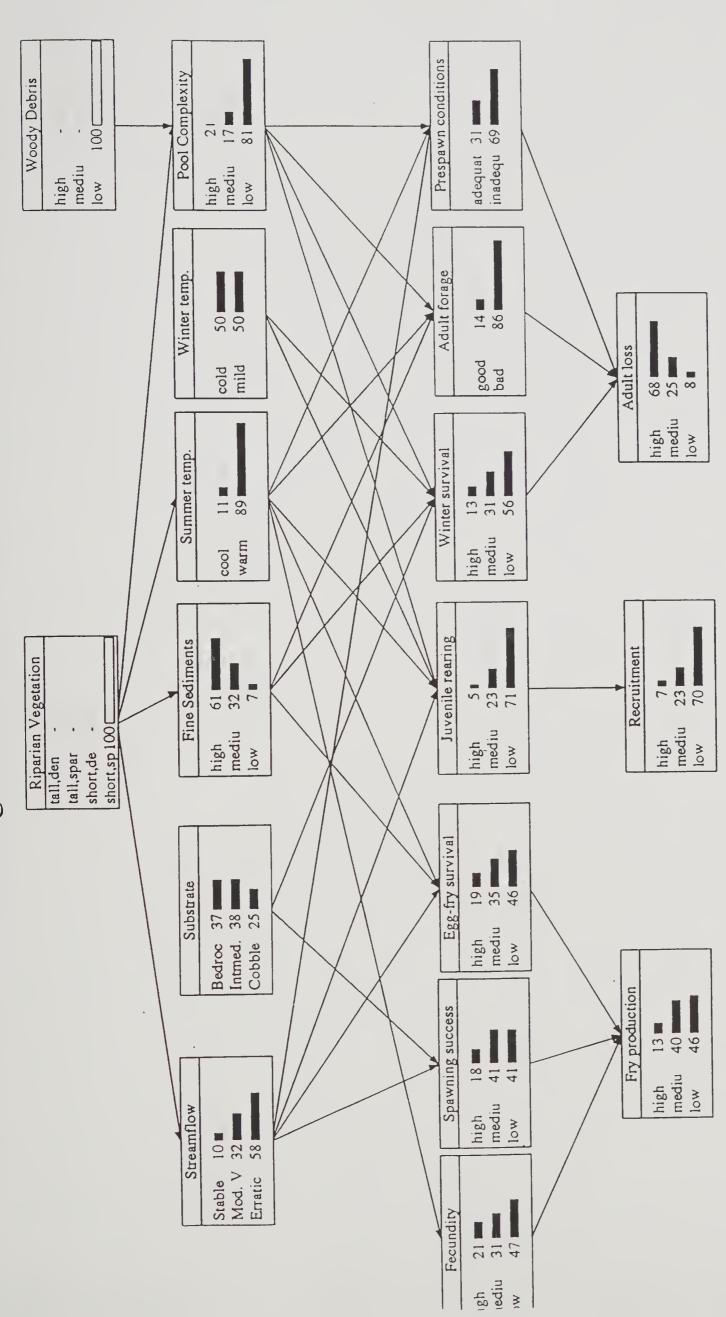
## BBN Linking Habitat to Fish Life History

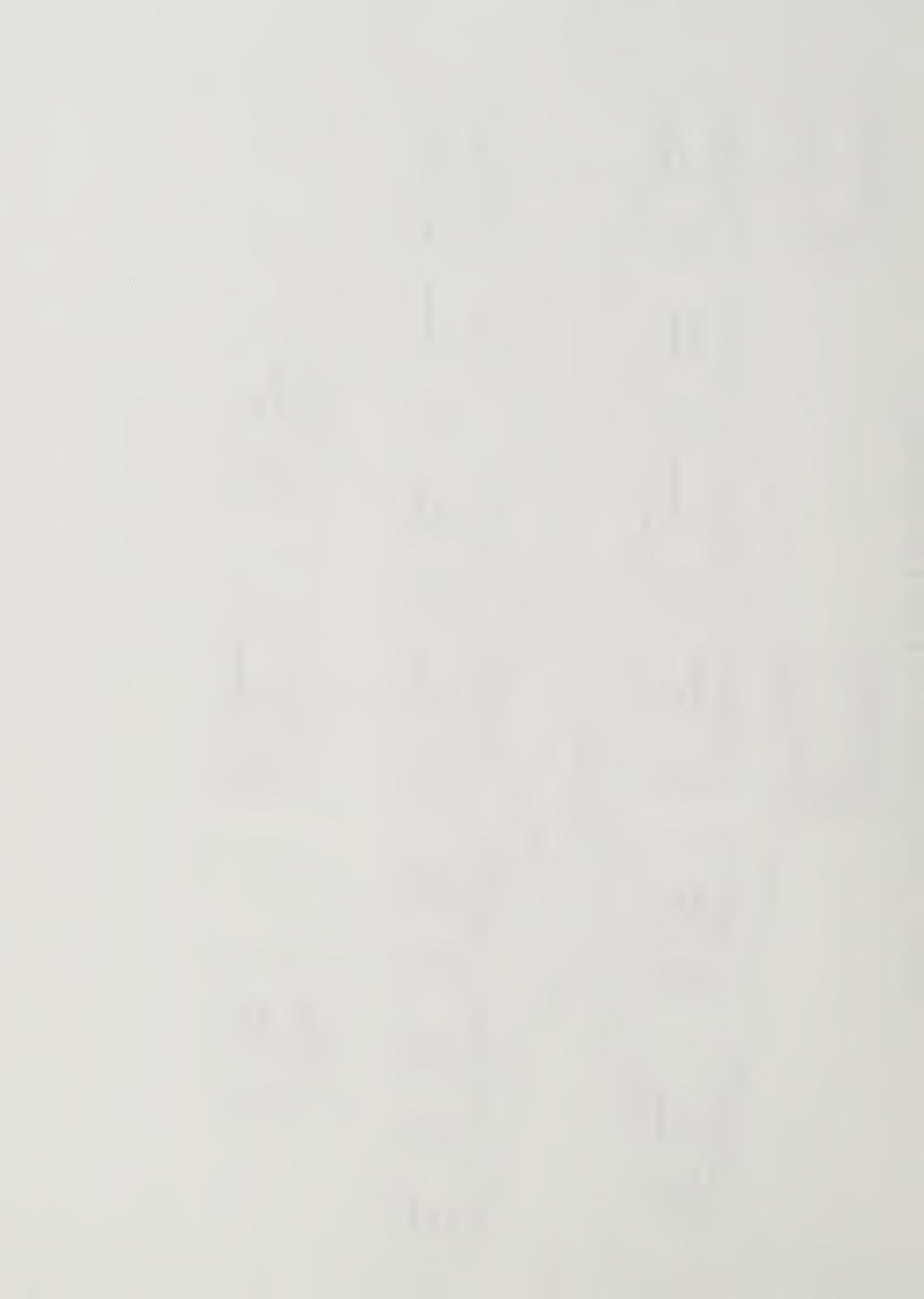












# BBN Linking Habitat to Fish Life History

